The SCENE Algorithm: High-Resolution IR/MW Sounding in the Presence of Clouds

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The SCENE Retrieval Algorithm

SC **Stochastic cloud clearing (Developed at MIT RLE)**

E **Eigenvector radiance compression and denoising**

NE **Neural network profile estimation**

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Outline

- Overview of SCENE algorithm
  - Stochastic cloud clearing
  - PPC compression
  - Multilayer feedforward neural networks
- Performance comparisons
  - Clear-air simulations over land
  - AIRS/ECMWF match-ups
- Error modeling
- Future Work

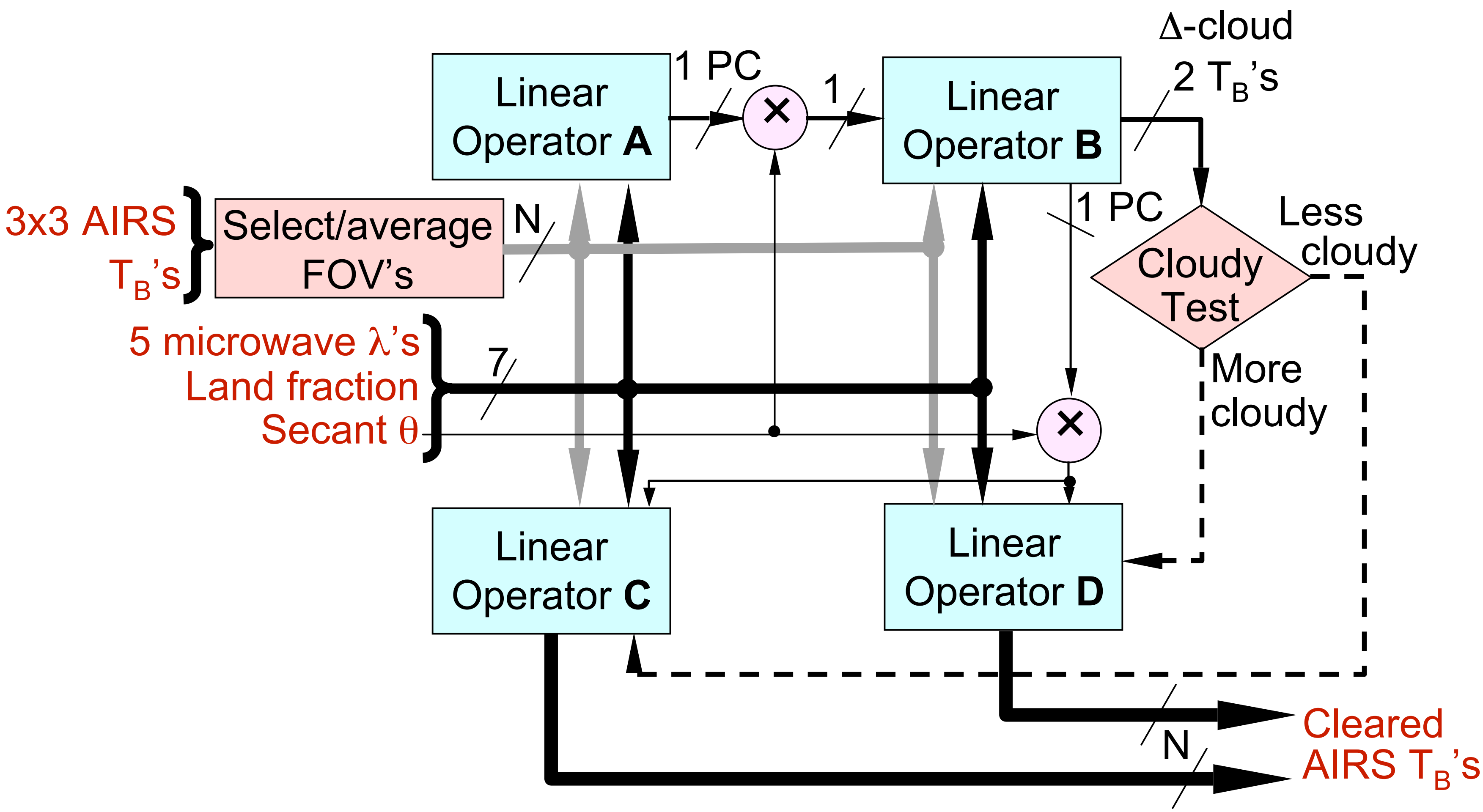
Stochastic Cloud Clearing (SCC)

- **How does stochastic clearing work?**
  - **SCC estimates cloud contaminations solely** based on statistics **without using any physical models**
  - **Hyperspectral measurements may contain sufficient information about clouds in an obscured manner**
  - Robust **and** stable **training is necessary**
  - **Nonlinearity is accommodated using stratification (sea/land, latitude, day/night), multiplicative scan angle correction, etc.**

- **Advantages of SCC approach**
  - Simple**: SCC does not require physical models (retrieval or radiative transfer).**
  - Fast**: Based on matrix addition and multiplication**

Cho and Staelin, Aug. 2005

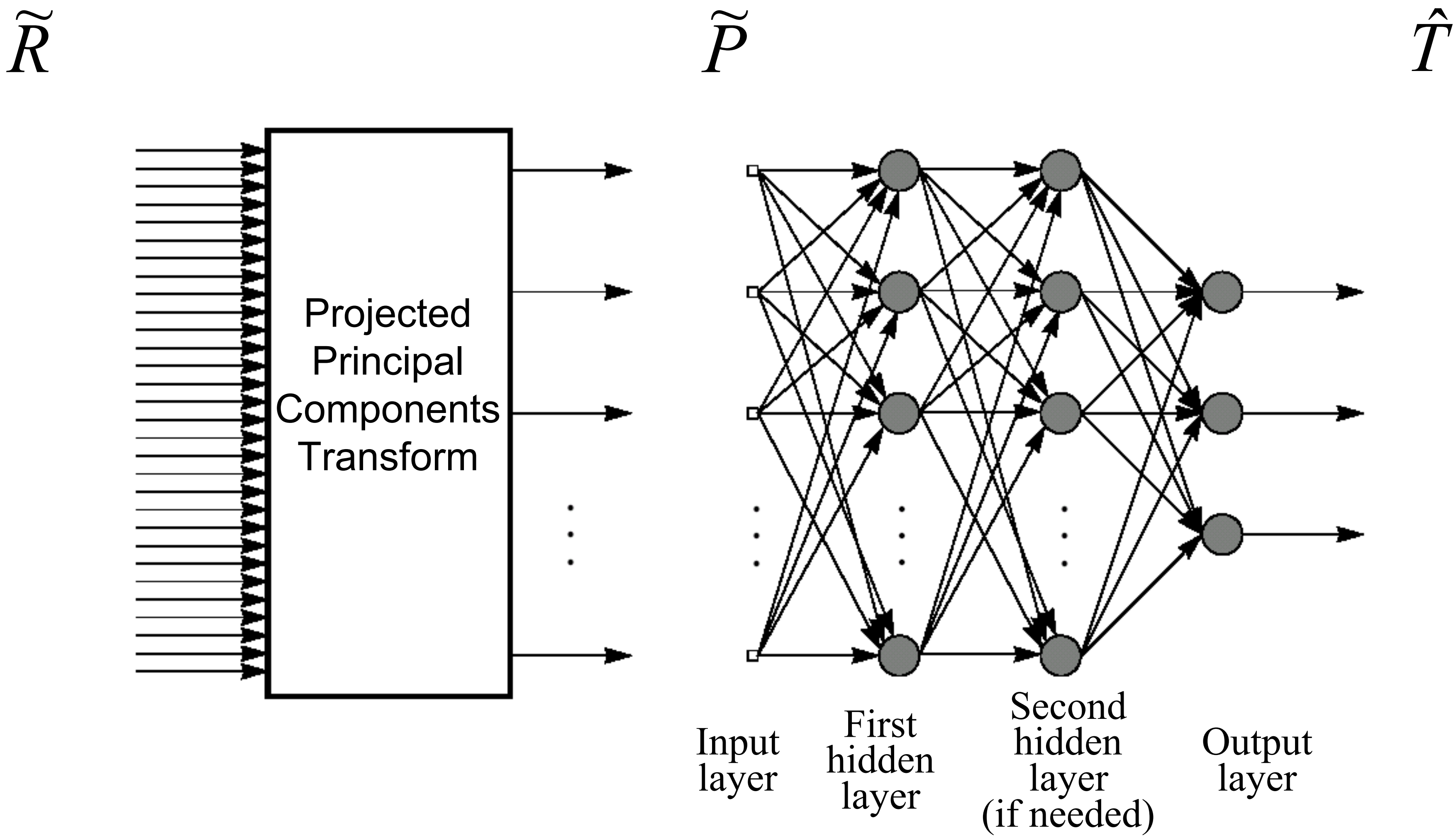
Block Diagram of SCC Algorithm



N = 314 channels

Cho and Staelin, Aug. 2005

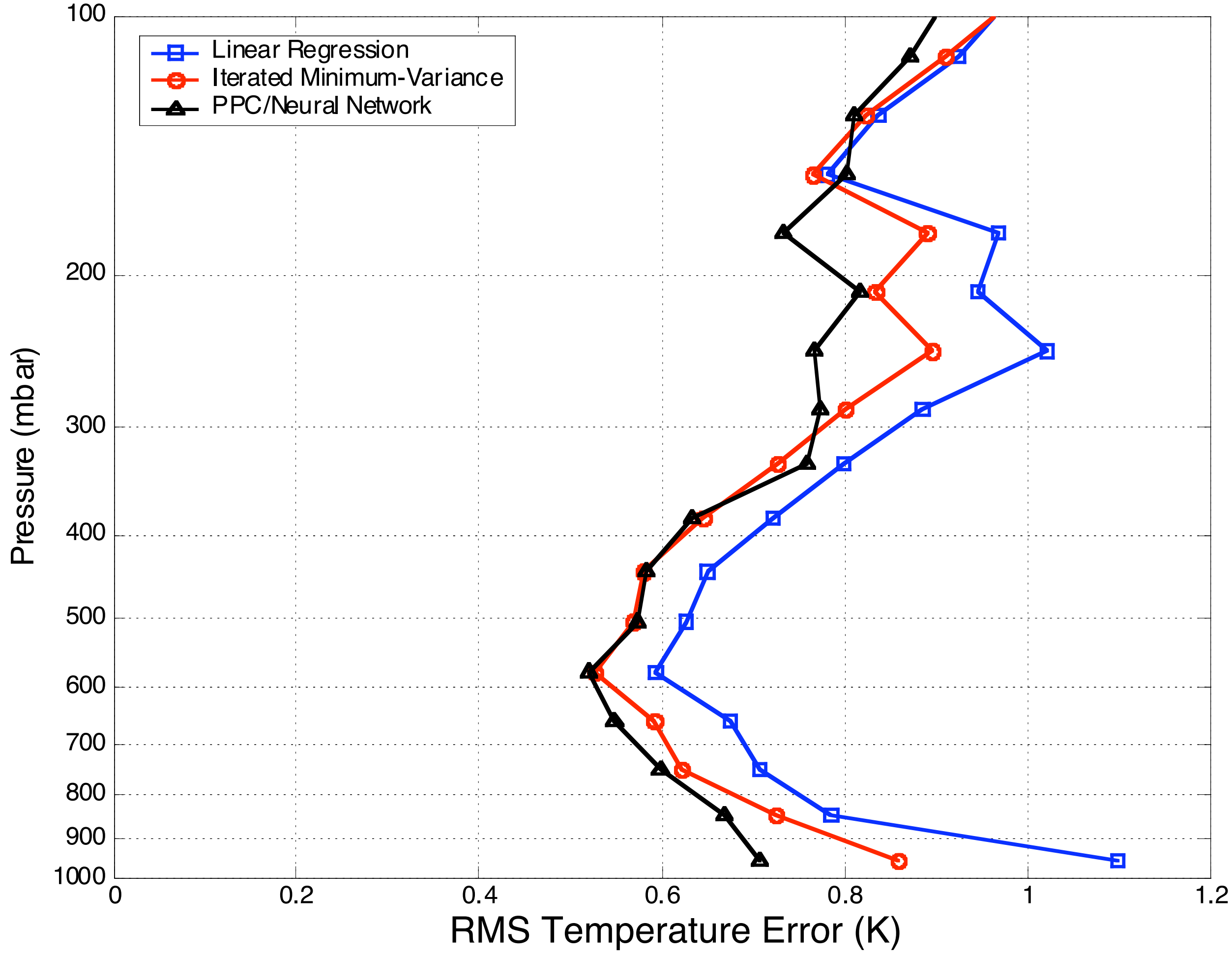
Combination of Compression and Neural Network



Performance Comparisons

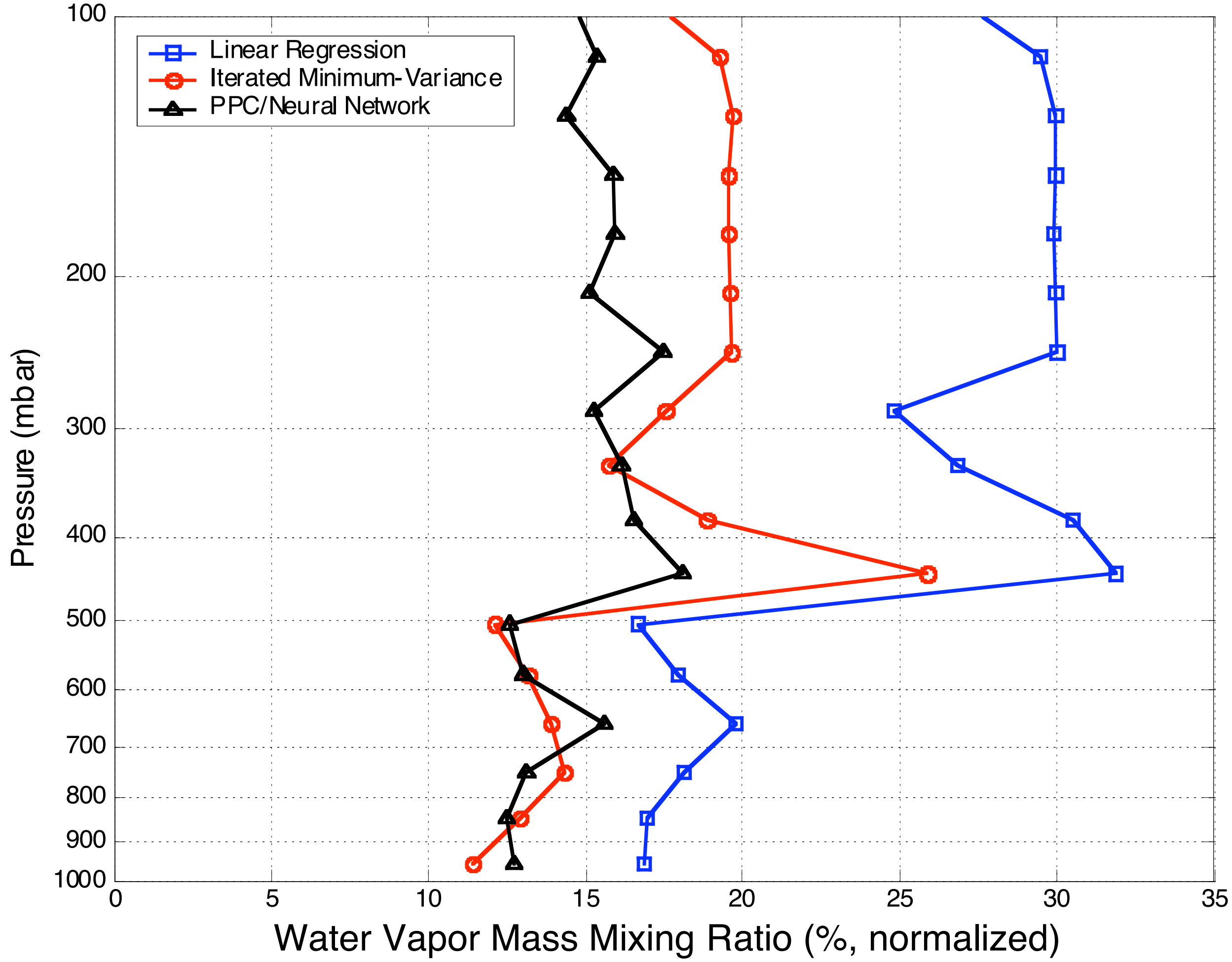
- Clear-air simulations
  - PPC/NN is compared with iterated “optimal estimation”
- AIRS/AMSU/ECMWF Match-ups
  - PPC/NN with stochastic cloud clearing (SCENE) is compared to ECMWF

Clear-Air Temperature Retrieval (Simulation)



AIRS channel set, NOAA88b raob set, land, daytime

Clear-Air Water Vapor Retrieval (Simulation)

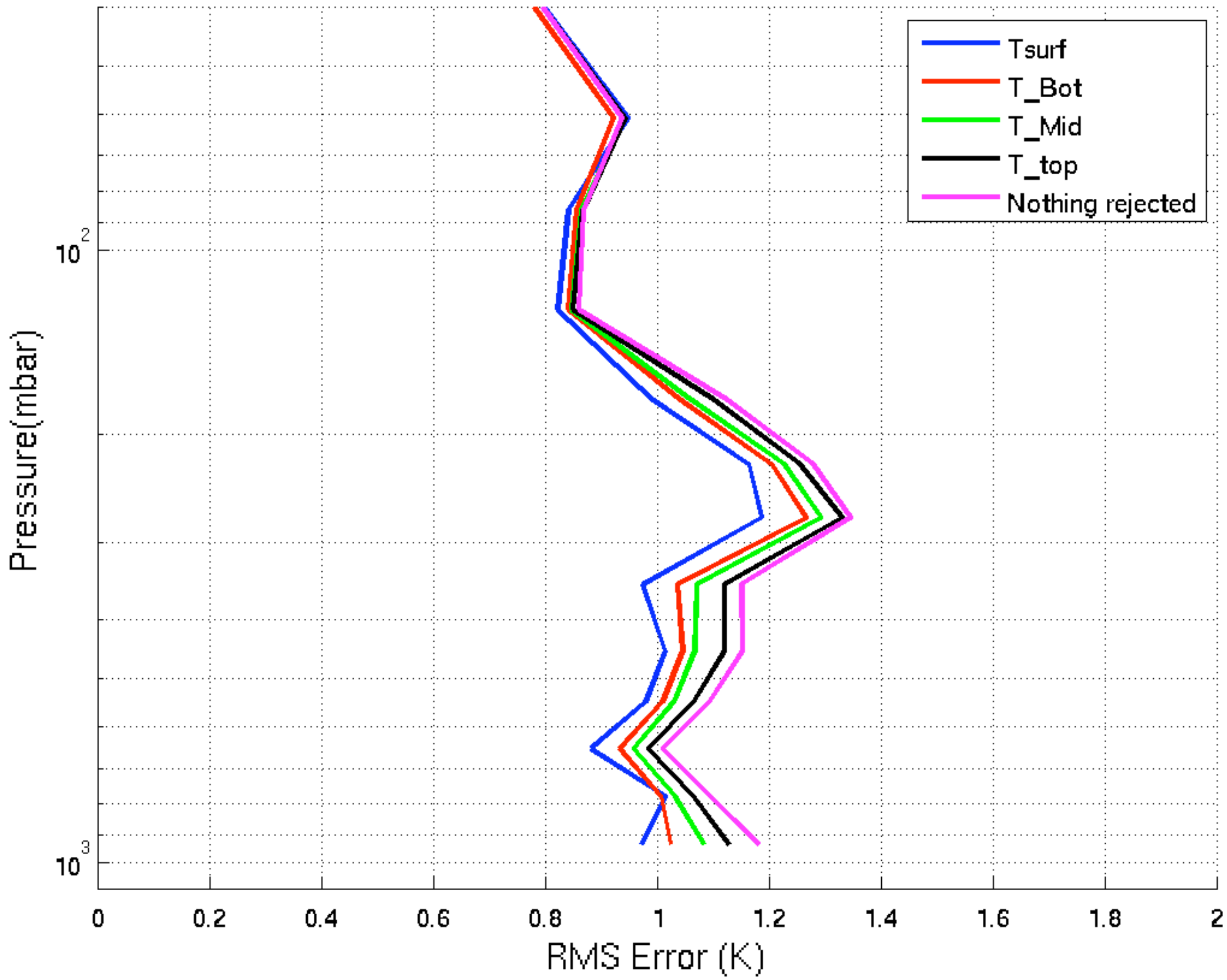


AIRS channel set, NOAA88b raob set, land, daytime

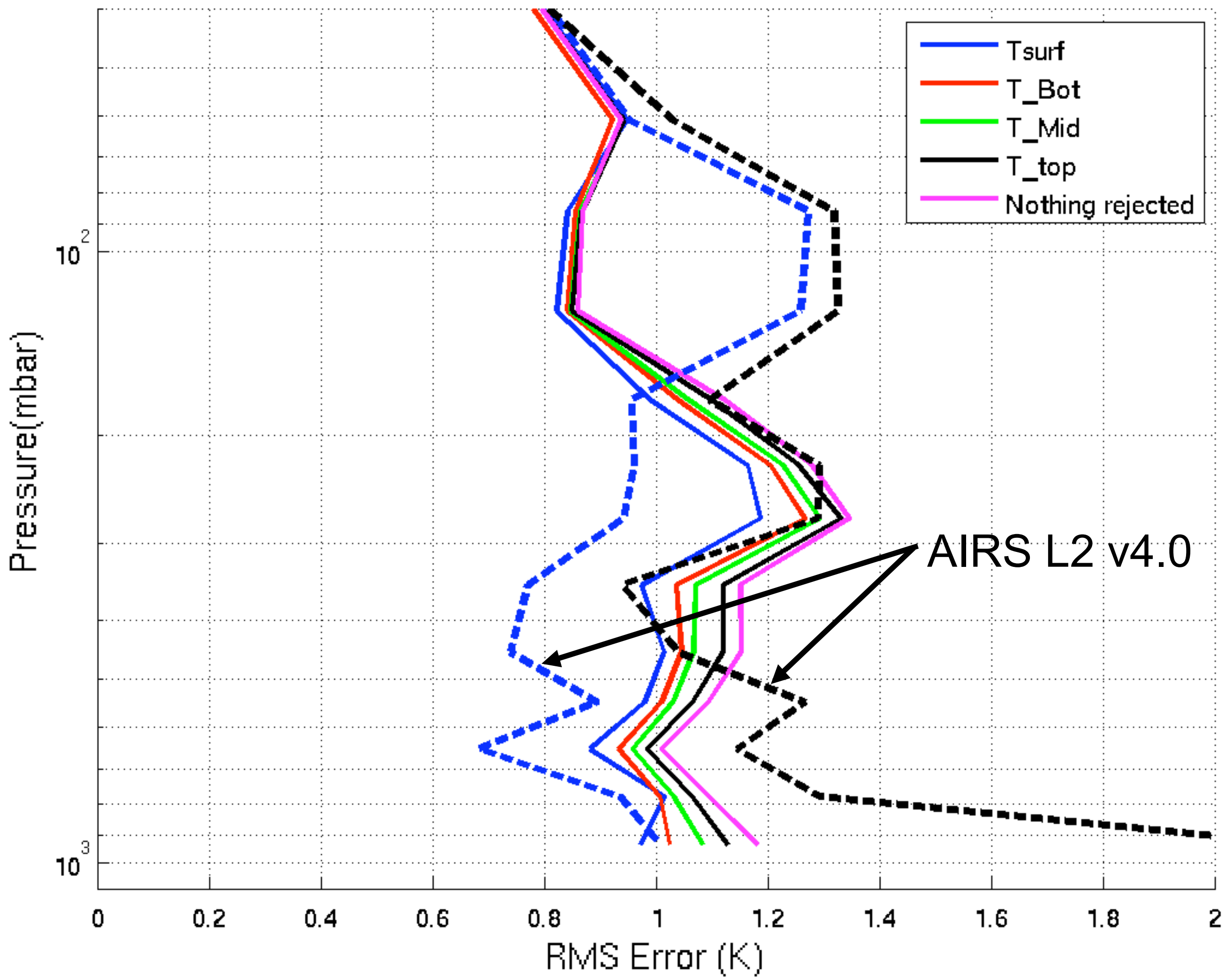
Retrieval Performance Validation with AIRS/AMSU/ECMWF Match-up Data

- 352,903 co-located AIRS/AMSU/ECMWF observations from seven days:
  - 2002: Sep 6
  - 2003: Jan 25, Jun 8, Aug 21, Sep 3, Oct 12, Dec 5
- 50,000 profiles set aside for validation set
- Ascending and descending orbits over land and ocean
- All scan angles
- Variable terrain elevation for PPC/NN (work in progress for SCENE)
- Latitudes arbitrarily restricted to ±60°

SCENE Temperature Profile Retrieval Ocean, Ascending, +/- 60 Latitude



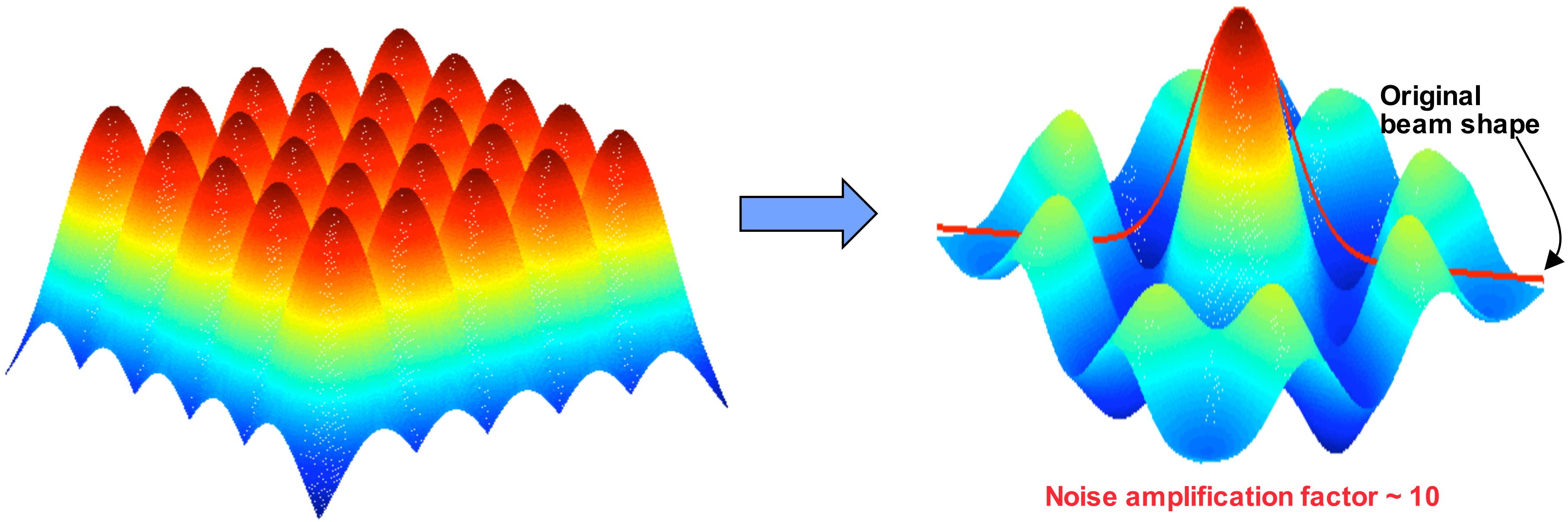
SCENE Temperature Profile Retrieval
Ocean, Ascending, +/- 60 Latitude



Other Advantages of SCENE

- SCENE is **FAST!!**
  - Using a desktop PC:
    - SCC can process one day in about three minutes
    - PPC/NN can process one day in about four minutes
    - SCENE can process one year in about one day
- SCENE is stable
  - Linear operators are used when possible
  - Nonlinear operators are used only when needed
- SCENE is flexible
  - Jacobians can be computed analytically
  - Algorithm parameters can be adjusted using design-of-experiments (DOE) approach

System Optimization Example: Spatial Filtering of ATMS



Noise amplification factor ~ 10

- **Optimize some aspect of the spatial response function**
  Trade off:
  - **Beam width**
  - **Measurement noise**
  - **Beam efficiency**
    - **Implications of "beam quality" vs. measurement noise trades on retrieved product not obvious**

Example: Backus-Gilbert

Propagation of Errors

Jacobian of retrieval model

Modeled retrieval error

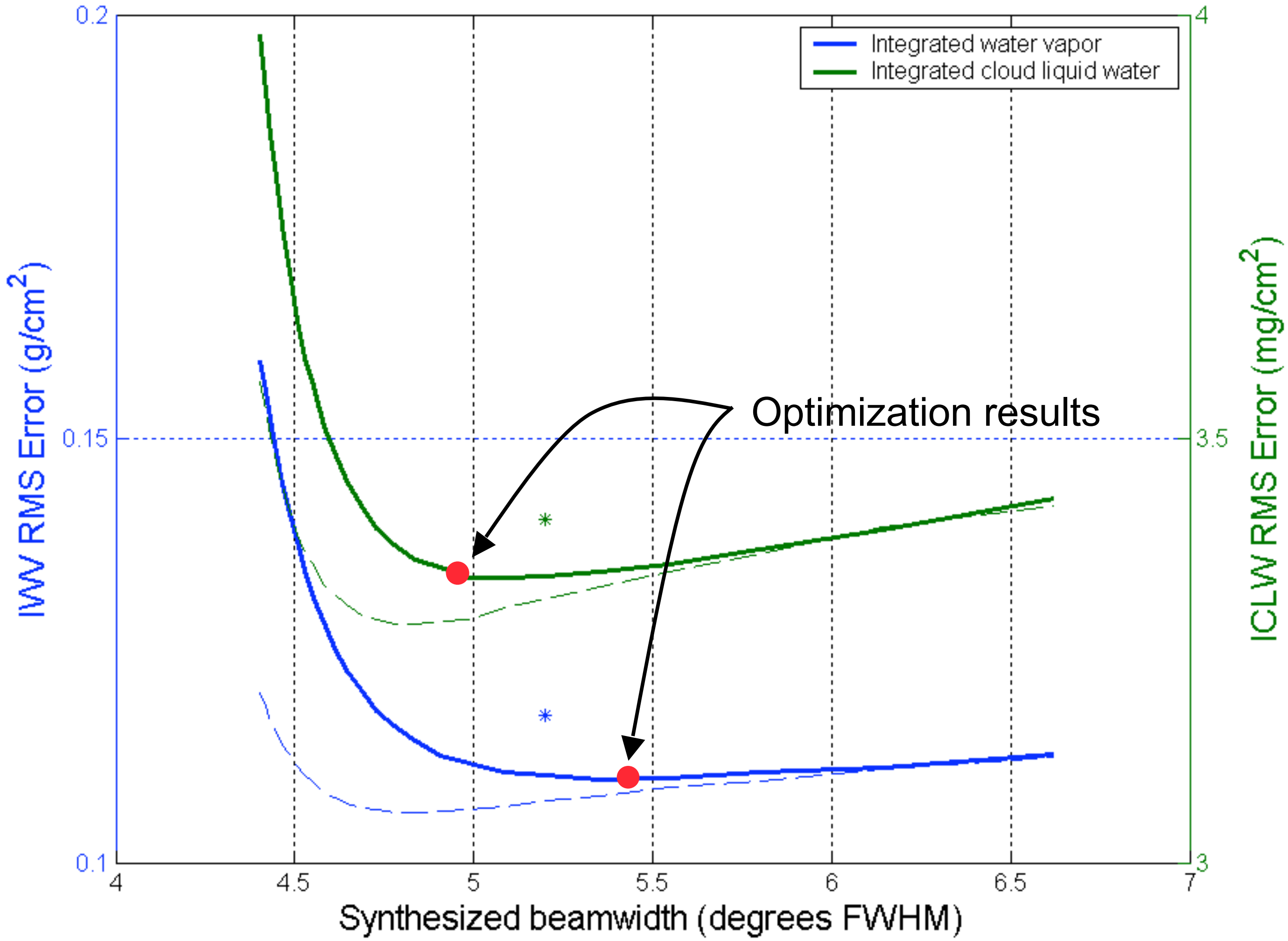
$$\varepsilon(\mathbf{h}) = \left[\frac{\partial f_o}{\partial \mathbf{h}}\right]^T \left[\mathbf{C}_{\text{Spatial}}^{(\mathbf{h})} + \mathbf{C}_{\text{Sensor}}^{(\mathbf{h})}\right]\left[\frac{\partial f_o}{\partial \mathbf{h}}\right]$$

$$\iint \Big(\sum_{i=1}^{N} h(i)\cdot T_B(i) - T_B^{\text{Hi-Res}}\Big)^2 dA$$

$$\sigma\, \mathbf{h}^T \mathbf{h}$$

ε(**h**) is minimized over **h**, subject to the constraint $\Sigma h(i) = 1$.

Results of Spatial Filter Optimization



Dashed lines indicate no sensor noise

Future Work

- **Additional and more extensive performance assessments**
  - Extend SCC evaluation to high latitudes and surface elevations
  - Additional match-ups with RAOB data
  - Comparisons with latest AIRS Level2 products (v4/v5)
- **Algorithm optimizations**
  - Improved performance over land
  - Improved quality assessment
  - Retrieval extensions to include ozone and trace gases
- **Adaptation of algorithm for CrIMSS**
  - Very helpful for system performance evaluations
  - Useful tool for cal/val

Recent Publications

- W. J. Blackwell, A Neural-Network Technique for the Retrieval of Atmospheric Temperature and Moisture Profiles from High Spectral Resolution Sounding Data, *IEEE Trans. Geosci. Remote Sensing,* vol. 43, no. 11, Nov. 2005.

- C. Cho and D. H. Staelin, Cloud clearing of AIRS Hyperspectral Infrared Radiances Using Stochastic Methods, *accepted for publication in JGR Atmospheres*.